Insurance-Based Credit Scores: Impact on Minority and Low Income Populations in Missouri

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Abstract and Overview

The widespread use of credit scores to underwrite and price automobile and homeowners insurance has generated considerable concern that the practice may significantly restrict the availability of affordable insurance products to minority and low-income consumers. However, no existing studies have effectively examined whether credit scores have a disproportionate negative impact on minorities or other demographic groups, primarily because of the lack of public access to appropriate data.

This study examines credit score data aggregated at the ZIP Code level collected from the highest volume automobile and homeowners insurance writers in Missouri. Findings—consistent across all companies and every statistical test—indicate that credit scores are significantly correlated with minority status and income, as well as a host of other socio-economic characteristics, the most prominent of which are age, marital status and educational attainment.

While the magnitude of differences in credit scores was very substantial, the impact of credit scores on pricing and availability varies among companies and is not directly examined in this study. The impact of scores on premium levels will be directly addressed in studies expected to be completed by late 2004.

Missouri statue prohibits sole reliance on credit scoring to determine whether to issue a policy. However, there are no limits on price increases that can be imposed due to credit scores, so long as such increases can be actuarially justified.

This study finds that:

1. **The insurance credit-scoring system produces significantly worse scores for residents of high-minority ZIP Codes.** The average credit score rank[1] in "all minority" areas stood at 18.4 (of a possible 100) compared to 57.3 in "no minority" neighborhoods – a gap of 38.9 points. This study also examined the percentage of minority and white policyholders in the lower three quintiles of credit score ranges; minorities were overrepresented in this worst credit score group by 26.2 percentage points. Estimates of credit scores at minority concentration levels other than 0 and 100 percent are found on page 8.

2. **The insurance credit-scoring systems produces significantly worse scores for residents of low-income ZIP Code.** The gap in average credit scores between communities with $10,953 and $25,924 in *per capita* income (representing the poorest and

[1] Results are presented here as ranks, or more accurately, *percentiles.* Because of significant differences in the scoring methods of insurers, many of the results in this report are presented as *percentiles* rather than as *percentage differences* in the raw credit scores. Anyone who has taken a standardized test should be familiar with the term. Scores for each company in the sample are ranked, and each raw score is then translated according to its relative position within the overall distribution. For example, a score ranked at the 75th percentile means that the score is among the top one-fourth of scores, and that 75 percent of recorded scores are worse. If the average for non-minorities was at the 30th percentile, and the minority average at the 70th percentile, the *percentile difference* is 40 percentiles. The *percentile difference*, calculated from the statistical models, is used herein as a convenient way to summarize results for the non-technical reader.

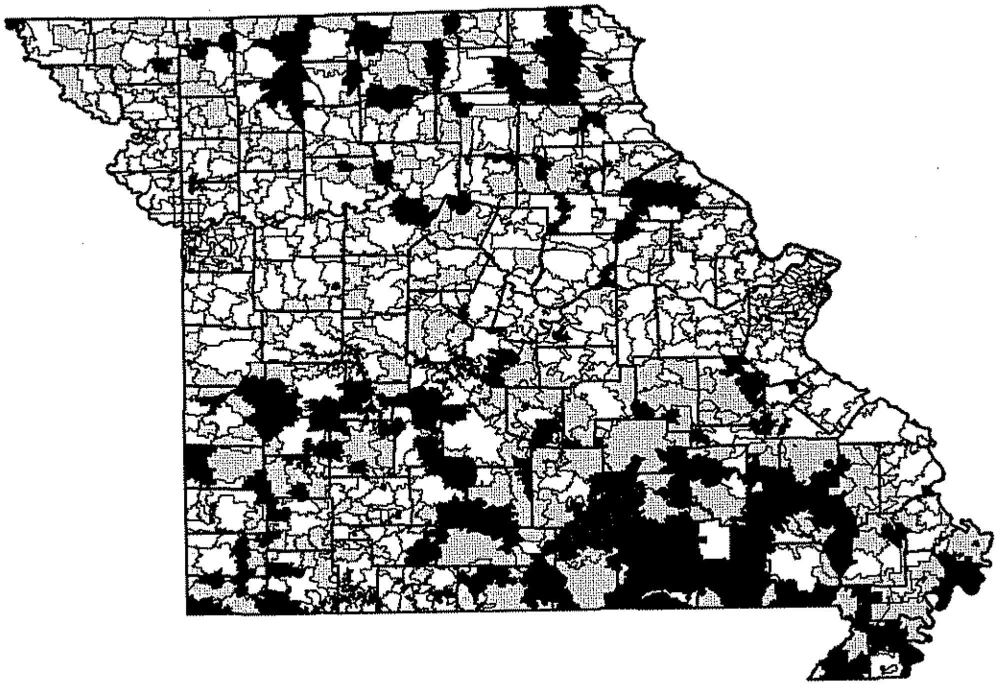
wealthiest 5 percent of communities) was 12.8 percentiles. Policyholders in low-income communities were overrepresented in the worst credit score group by 7.4 percentage points compared to higher income neighborhoods. Estimates of credit scores at additional levels of *per capita* income are found on page 9.

3. **The relationship between minority concentration in a ZIP Code and credit scores remained after eliminating a broad array of socioeconomic variables, such as income, educational attainment, marital status and unemployment rates, as possible causes.** Indeed, minority concentration proved to be the single most reliable predictor of credit scores.

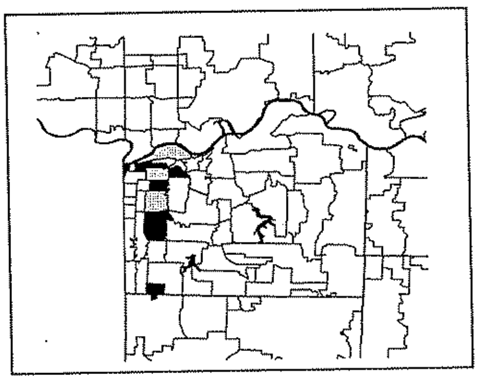
4. **Minority and low-income *individuals* were significantly more likely to have worse credit scores than wealthier individuals and non-minorities.** The average gap between minorities and non-minorities with poor scores was 28.9 percentage points. The gap between individuals whose family income was below the statewide median versus those with family incomes above the median was 29.2 percentage points.

The following maps indicate the areas in Missouri that are most negatively affected by the use of credit scores.

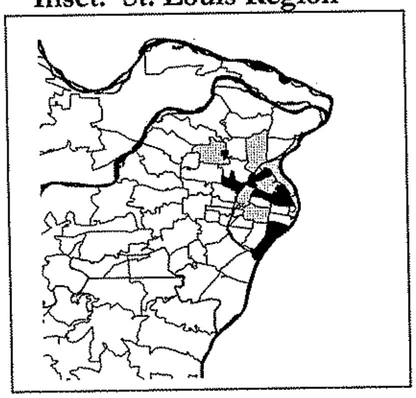
Lower Income Areas of Missouri Most Affected by Credit Scoring



Inset: Kansas City Region



Inset: St. Louis Region

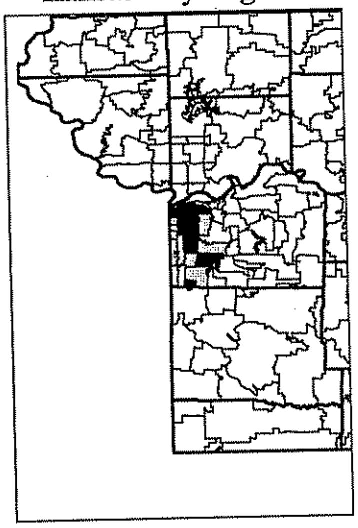


Bottom Quartile ($6,153 - $13,335) = 253 Zip Codes (out of 1,015), with 562,453 persons, or 10% of 5.6 million Missourians

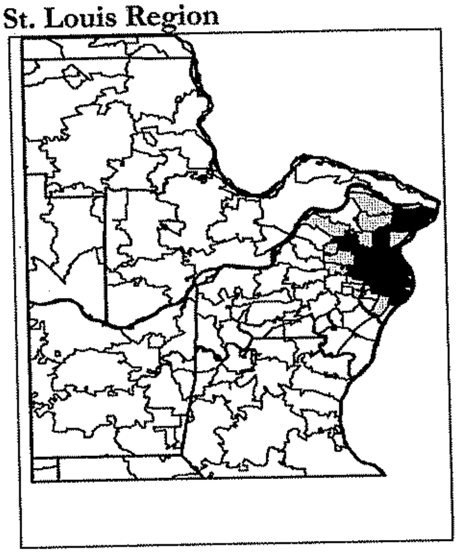
Second Quartile ($13,336-$15,326) = 254 ZIP Codes with 839,281 persons, or 15% of 5.6 million Missourians

Areas of Missouri With High Minority Concentration Most Affected by Credit Scoring

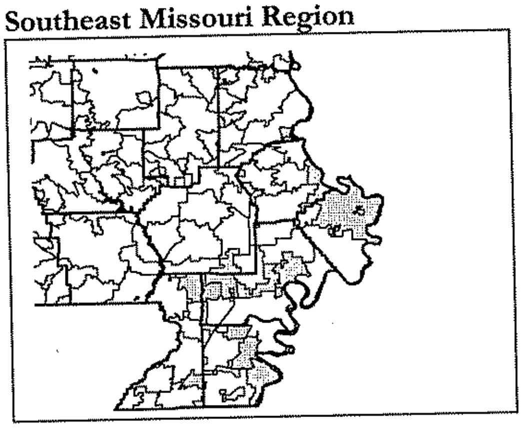
Kansas City Region

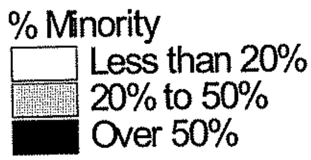


St. Louis Region



Southeast Missouri Region





Missourians in High-Minority ZIP codes

% Minority	White, Non-Hispanic	African-Americans and Hispanics	Other	Total
20% to 50%	337,631	165,441	11,953	515,025
Over 50%	134,541	397,430	10,817	542,788
Total Missouri Population	**4,687,837**	**815,325**	**92,049**	**5,595,211**

Executive Summary

The use of individuals' credit histories to predict the risk of future loss has become a common practice among automobile and homeowners insurers. The practice has proven to be controversial not only because of concerns about how reliably credit scores may predict risk. Many industry professionals, policymakers, and consumer groups have expressed concern that the practice may pose a significant barrier to economically vulnerable segments of the population in obtaining affordable automobile and homeowners coverage.

This study finds evidence that justifies such concerns.

Four questions are addressed in the study:

1. Is there a correlation between place of residence and insurance-based credit scores (called "credit scores" or "scores" throughout the remainder of this report)? Specifically, do residents of areas with high minority concentrations have worse average scores?

2. Do residents of poorer communities have worse average scores?

3. If credit scoring has a disproportionate impact on residents of communities with high minority concentrations, what other socioeconomic factors might account for this fact?

4. Do minorities and poorer individuals tend to have worse scores than others, irrespective of place of residence?

For this report, the category 'minority' includes all Missourians who identified themselves as African-American or Hispanic in the 2000 census. A separate analysis of African-Americans resulted in no substantive difference from the results presented here.

Data

Credit score data was solicited from the 20 largest automobile and homeowners writers in Missouri for the period 1999-2001. Of these, 12—individually or combined with sister companies—had used a single credit scoring product for a sufficient period of time to generate a credible sample. In some instances, a single company is displayed as two separate "companies" representing separate analyses of automobile and homeowners coverage. In other instances, sister companies were combined to yield a more statistically credible sample. The net result of these combinations is the 12 "companies" presented in the report.

Companies That Submitted Data for this Report

NAIC Code	Name
16322	Progressive Halcyon Insurance Co.
17230	Allstate Property & Casualty Insurance Co.
19240	Allstate Indemnity Co.
21628	Farmers Insurance Co., Inc.
21660	Fire Insurance Exchange
21687	Mid-Century Insurance Co.
22063	Government Employees Insurance Co.
25143	State Farm Fire And Casualty Co.
25178	State Farm Mutual Automobile Insurance Co.
27235	Auto Club Family Insurance Co.
35582	Government General Insurance Co.
42994	Progressive Classic Insurance Co.

Additional information about how the Missouri's largest insurers use credit scores can be found at the MDI web site, www.insurance.mo.gov.

The companies provided average credit scores by ZIP Code, as well as the distribution of exposures (automobiles and homes) across five credit score intervals representing equal numeric ranges. Both the average score and the percent of exposures in the worst three intervals are used to assess to the degree to which race and ethnicity and socioeconomic status are correlated with credit scores.

Because of the nature of the data, results are presented from two categorically distinct levels of analysis:

1. *Aggregate level*—Inferences about **residents in areas with high minority concentrations or areas with lower incomes.** This level of analysis does not purport to make inferences about minority or lower-income individuals *per se.*

2. *Individual level*—Assessments of the likely impact of credit scores on minority **individuals,** without reference to place of residence. These results make use of statistical models that are widely employed in the social sciences, but findings are somewhat more speculative than are the aggregate level results.

Findings

1. On average, residents of areas with high minority concentrations tend to have significantly worse credit scores than individuals who reside elsewhere.

2. On average, residents of poor communities tend to have significantly worse credit scores than those who reside elsewhere.

Given the variation in credit scoring methodologies, raw credit scores possess no intrinsic meaning, and comparing raw scores across companies is of limited value. Normalized or "standardized" results afford more meaningful comparisons. Averaged across all companies, the spread in standardized scores between "no minority" and "all minority"[2] ZIP Codes was 38.9 percentiles—a very considerable gap.[3] For more than half of the companies, the average scores of individuals residing in minority ZIP Codes fell into the bottom one-tenth of scores (that is, at or lower than the 10th percentile). The average score of individuals residing in non-minority ZIP Codes fell into the upper one-half of scores for every company.

The last three columns of the table display percentile differences by income group. On average, ZIP Codes with a *per capita* income of $25,924 (the top 5 percent of ZIP Codes) had scores that were 12.8 percentiles higher than ZIP Codes with a *per capita* income of $10,953 (the bottom 5 percent of ZIP Codes).

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[2] The statistical models incorporate data from all ZIP Codes to determine the overall relationship between minority concentration and credit scores. Estimates derived from the models are presented here at the extremes of 0 percent and 100 percent minority concentration for expository reasons (the meaning of values at the extremes is usually more intuitive). For example, if the regression model indicated that every percentage point increase in minority concentration is associated with a decrease in credit scores of 1.68 points, the impact of increasing minority concentration to 100 percent would be a decline of 168 points. In reality, there are no ZIP Codes whose residents are all minorities, though several ZIP Codes have more than 95 percent minority concentration.

[3] Percentile differences are based on normalized scores ranging from 0 to 100, and represent the rank of a score relative to all other scores in the sample. Such percentiles are exactly analogous to those used for reporting standardized test results. For example, a score falling in the 75th percentile means the score is among the top one-fourth of scores. The numbers reported in the table below represent the percentile difference between high and low minority ZIPs. For example, if the average score of high minority ZIP Codes was at the 20th percentile, and those for low minorities at the 80th percentile, the difference is 60 percentiles.

Standardized Credit Scores (Percentiles) by Minority Concentration and *Per Capita* Income in ZIP Code

Results of Weighted OLS Regression of Average Credit Score
Scores Coded So that a *Lower* Score is *Worse*

	Average Score Percentile by Minority Concentration (on a scale of 100)			Average Score Percentile by *Per Capita* Income (on a scale of 100)		
Company[4]	100% Minority	0% Minority	Percentile Difference	$10,953 (Poorest 5% of ZIP Codes)	$25,924 (Wealthiest 5% of ZIP Codes)	Difference
A	24.2	54.0	29.8	35.9	51.6	15.7
B	2.1	59.5	57.4	37.8	52.4	14.6
C	5.8	59.1	53.4	30.5	52.4	21.9
D	11.9	56.4	44.5	44.4	52.8	8.4
E	12.3	57.9	45.6	46.8	54.8	8.0
F	30.5	59.5	29.0	46.0	57.9	11.9
G	29.1	59.1	30.0	42.9	56.8	13.9
H*	22.4	56.0	33.6	45.2	52.8	7.6
I*	33.0	50.8	17.8	41.3	48.0	6.7
J	14.2	59.9	45.6	40.5	55.2	14.7
K	25.1	55.6	30.4	44.0	53.6	9.6
L	9.7	59.5	49.8	34.8	55.2	20.3
Average (Unweighted)	**18.4**	**57.3**	**38.9**	**40.9**	**53.6**	**12.8**

**These two companies were unable to provide MDI with raw credit scores. Data thus consists of scores that have been furthered modified based on non-credit related information prior to being used for rating / underwriting.*

In addition to average credit scores by ZIP Code, the number of exposures[5] in five equal credit score intervals was also collected; each interval represents the range of scores divided by five.[6] The proportion of exposures in the worst three intervals was used, as a parallel measure to average scores, to assess the association between race and income and credit scores. On average, a 26.2 percentage point difference existed in the proportion of exposures in the worst credit score group between "all minority" and non-minority ZIP Codes. The corresponding gap between the wealthiest and poorest income groups was 7.4 percentage points.

Estimates for additional levels of minority concentration and *per capita* income are displayed in the following four tables.

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[4] This report represents an analysis of credit scoring in general, and not the compliance of a specific company with any laws, nor the degree to which a company deviated from the norm. Thus, no individual companies are identified when displaying results.

[5] One "exposure" is equal to one year of coverage for one automobile or home.

[6] For clarification, credit score intervals are not quintiles where each interval represents an equal number of exposures. Rather, each interval is an equal numeric range in credit scores, and exposures are not distributed equally between intervals.

Percent of Exposures in Worst 3 Credit Score Intervals by % Minority and *Per Capita* Income in a ZIP Code

Results of Weighted OLS Regression

	Scores in Worst Group by Percent Minority			Scores in Worst Group by *Per Capita* Income		
Company	0% Minority	100% Minority	Difference	$10,953 (Poorest 5% of ZIP Codes)	$25,924 (Wealthiest 5% of ZIP Codes)	Difference
A	41.4%	64.8%	23.4%	52.4%	44.4%	8.0%
B	8.9%	53.7%	44.9%	19.4%	12.5%	6.9%
C	20.5%	61.7%	41.2%	35.8%	25.1%	10.7%
D	26.7%	57.2%	30.6%	34.4%	28.2%	6.2%
E	33.7%	73.2%	39.5%	42.6%	35.9%	6.7%
F	38.9%	62.3%	23.5%	50.9%	39.5%	11.3%
G	14.5%	31.9%	17.4%	22.9%	16.2%	6.7%
H	21.7%	37.1%	15.5%	26.7%	22.9%	3.8%
I	68.3%	79.7%	11.4%	75.0%	68.0%	7.0%
J	12.1%	30.4%	18.3%	19.0%	13.8%	5.2%
K	13.2%	28.4%	15.2%	18.6%	14.2%	4.4%
L	21.8%	55.5%	33.7%	35.9%	24.1%	11.8%
Average (Unweighted)	**26.8%**	**53.0%**	**26.2%**	**36.1%**	**28.7%**	**7.4%**

Standardized Credit Scores (Percentiles) by % Minority in a ZIP Code

Results of Weighted OLS Regression of Average Credit Score

Scores Coded So that a *Lower* Score is *Worse*

Company	0% Minority	25% Minority	50% Minority	75% Minority	90% Minority	100% Minority
A	54.0	46.0	38.2	30.9	26.8	24.2
B	59.5	37.1	18.4	7.2	3.6	2.1
C	59.2	41.3	24.2	13.1	8.2	5.8
D	56.4	42.9	30.5	20.1	14.9	11.9
E	57.9	44.4	31.6	20.6	15.2	12.3
F	59.5	48.0	44.8	37.5	33.0	30.5
G	59.1	48.4	43.6	36.3	31.9	29.1
H	56.0	46.8	37.8	29.8	25.1	22.4
I	50.8	46.0	41.7	37.1	34.5	33.0
J	59.9	46.8	34.1	23.0	17.4	14.2
K	55.6	47.6	39.4	31.9	27.8	25.1
L	59.5	44.0	29.8	17.9	12.5	9.7
Average	57.3	44.9	34.5	25.4	20.9	18.4

Percent of Exposures in Worst 3 Credit Score Intervals by % Minority in a ZIP Code

Results of Weighted OLS Regression

Company	0% Minority	25% Minority	50% Minority	75% Minority	90% Minority	95% Minority	100% Minority
A	41.4	47.2	53.1	58.9	62.4	63.6	64.8
B	8.9	20.1	31.3	42.5	49.2	51.5	53.7
C	20.5	30.8	41.1	51.4	57.6	59.6	61.7
D	26.7	34.3	42.0	49.6	54.2	55.7	57.2
E	33.7	43.6	53.5	63.3	69.2	71.2	73.2
F	38.9	44.7	50.6	56.5	60.0	61.2	62.3
G	14.5	18.9	23.2	27.6	30.2	31.0	31.9
H	21.7	25.5	29.4	33.3	35.6	36.4	37.1
I	68.3	71.2	74.0	76.9	78.6	79.2	79.7
J	12.1	16.7	21.2	25.8	28.5	29.5	30.4
K	13.2	17.0	20.8	24.6	26.9	27.6	28.4
L	21.8	30.2	38.6	47.1	52.1	53.8	55.5
Average	26.8	33.4	39.9	46.4	50.4	51.7	53.0

Standardized Credit Scores (Percentiles) by *Per Capita* Income in ZIP Code

Results of Weighted OLS Regression of Average Credit Score

Scores Coded So that a *Lower* Score is *Worse*

Company	Bottom 1% ($8,642)	Quartile 1 ($13,335)	Quartile 2 ($15,326)	Quartile 3 ($18,092)	Top 1% ($50,536)
A	33.4	38.2	40.5	43.3	76.1
B	35.9	40.1	42.1	44.8	74.5
C	27.4	33.7	36.7	40.5	84.1
D	43.3	45.6	47.2	48.4	65.9
E	45.2	48.0	49.2	50.4	67.7
F	44.0	48.0	49.6	51.6	75.5
G	40.9	45.2	46.8	49.6	76.7
H	44.0	46.4	47.6	48.8	64.4
I	40.1	42.5	43.3	44.4	59.1
J	38.2	42.9	44.8	47.6	77.0
K	42.5	45.6	46.8	48.4	68.4
L	31.9	37.8	40.5	48.8	83.7
Average (Unweighted)	**38.9**	**42.8**	**44.6**	**47.2**	**72.8**

Percent of Exposures in Worst Three Credit Score Intervals
by *Per Capita* Income a ZIP Code
Results of Weighted OLS Regression

Company	Bottom 1% ($8,642)	Quartile 1 (13,335)	Quartile 2 (15,326)	Quartile 3 (18,092)	Top 1% (50,536)
A	53.6	51.1	50.1	48.6	31.6
B	20.5	18.3	17.4	16.1	1.4
C	37.4	34.1	32.6	30.7	7.9
D	35.3	33.4	32.6	31.4	18.3
E	43.6	41.5	40.6	39.4	25.1
F	52.6	49.1	47.6	45.5	21.3
G	23.9	21.8	20.9	19.7	5.4
H	27.3	26.1	25.6	24.8	16.7
I	76.1	73.9	73.0	71.7	56.8
J	19.8	18.2	17.5	16.5	5.5
K	19.3	17.9	17.3	16.5	7.2
L	37.7	34.0	32.4	30.2	5.1
Average (Unweighted)	**37.3**	**34.9**	**34.0**	**32.6**	**16.9**

3. Credit scores are significantly correlated with minority concentration in a ZIP Code, even after controlling for income, educational attainment, marital status, urban residence, the unemployment rate and other socioeconomic factors.

Statistical models were used to control for—i.e., remove—the impact of socioeconomic factors that might account for the correlation between race/ethnicity and credit scores. The inclusion of such controls slightly weakened, but by no means eliminated (or accounted for) the association between minority status and credit scores. Among all such control variables, race/ethnicity proved to be the most robust single predictor of credit scores; in most instances it had a significantly greater impact than education, marital status, income and housing values. It was also the only variable for which a consistent correlation was found across all companies.

Other variables found to be significantly correlated with credit scores across the majority of companies were educational attainment, age, marital status, and urban residence.

Why scores should be correlated with minority status, even after controlling for such broad measures of socioeconomic status, is not immediately clear. Such a result indicates that the variable "minority concentration" contains unique characteristics not contained in the "control" variables. For example, credit scores may reflect factors uniquely associated with racial status (such as limited access to credit, for example). The results clearly call for further study.

4. The minority status and income levels of *individuals* are correlated with credit scores, regardless of place of residence.

Three different statistical models were used to assess differences in scores between minority and low-income **individuals,** as opposed to **residents of high minority or low-income areas** (not all of whom, of course, are minorities or poor). **Based on the most credible of the three models, African-American and Hispanic insureds had scores in the worst credit score group at a rate of about 30 percentage points higher than did other individuals (for example, where 30 percent of one group may have poor scores, compared to 60 percent of another group). A gap of 30 percentage points also existed between individuals earning below and above the median family income for Missouri.** Across companies, the gap for minority status ranged from 14 percent to 48 percent; and for income the gap ranged from 17 to 46 percent.

Difference in % of individuals in the worst 3 (of 5) credit score intervals
Estimates of Gary King's Ecological Inference (EI) Model[7]

Company	Minority Status (% of minorities with low scores minus % of non-minorities with low scores)	Income (% of lower-income individuals with low scores minus % of higher-income individuals with low scores)
A	19.1%	27.7%
B	39.5%	16.8%
C	42.1%	46.1%
D	30.6%	22.5%
E	47.9%	28.5%
F	25.8%	35.6%
G	14.5%	21.0%
H	29.1%	32.8%
J	15.0%	26.7%
K	15.3%	26.4%
L	38.5%	37.2%
Unweighted Average	**28.9%**	**29.2%**

[7] The EI model is one of three employed in this report to make individual-level inferences. The other two are Goodman's Regression and the "Neighborhood" model, each of which is explained in the body of the report.

While considerable variation exists among the three models with respect to the magnitude of estimates, all three consistently estimated a disproportionate impact based on the minority status of individuals and an individual's family income.

Because the data is composed of ZIP Code level aggregates, inferences about individual-level characteristics are somewhat more speculative than are inferences about the demographic characteristics of place of residence. Individual-level estimates in this report result from three of the most widely-used statistical models for such purposes. *While the model results are not "proof" of an* ***individual-level*** *disproportionate impact, the evidence appears to be substantial, credible and compelling.*